Holistic Player Evaluation with RIPP: Region-based Isolated Player Performance

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1 Introduction

Evaluating players is a difficult challenge in hockey analytics due to the low frequency of goals. Modern day player evaluation paradigms in hockey are much like the models used in the pre-money-ball era of baseball. It is common to see models which derive player value entirely from goals, assists or other rare events.

We propose a holistic framework which leverages data to better represent an individual player's value as a sum of expected goal differentials resulting from actions made by that player. This framework allows analysts to attach value to a greater variety of player actions, including passes and turnovers.

We present a proof-of-concept for our framework by implementing a simple version of our model using play-by-play data from women's hockey games. This implementation is used to illustrate how our framework might allow hockey analysts to evaluate player actions beyond classic box score metrics such as goals and assists.

2 Relevant Work

There have been a number of other papers which proposed player evaluation models. A 2018 paper proposed that a weighted average of goal, assists, penalties, and other metrics should be used to evaluate NWHL player performance [1]. The downside to an approach like this is that the estimated player performance is largely dependent on the performance of a player's other teammates.

Another common approach for player valuation in team sports is a framework that considers the "expected possession value". Players accrue credit by advancing the ball or puck from a less desirable state to a more desirable one. This approach has been successfully applied across a number of sports, including soccer [7] and basketball [8]. In hockey, [2] attempt to isolate individual player performance, but require an extensive number of input parameters. This makes it challenging to identify which individual factors contribute to a player's value. Our paper proposes a method for isolating individual player performance while requiring fewer parameters, allowing for a transparent view of what factors are contributing to a player's value.

3 Framework

Our system creates a catch-all statistic to determine how well a player performs in each game. In our framework, we develop a set of possible states in which the game may be at a given moment in time. Each state is associated with a value indicating the probability that the team in possession scores from that situation. Then, for each player action, we assign a score as the difference in value between the end state and start state of the action. Since we envision the state space relying heavily on the location of the puck within the rink, we call this metric RIPP, standing for "region-based isolated player performance".

To compute RIPP, we must first establish the set of states and corresponding values. A naive model might consider only two states, indicating which team has possession. Under this setup, only actions that result in a change of possession have non-zero RIPP.

A slightly more useful state space might include the zone of the rink in which the puck is located. For each zone, the probability of a possession that enters that zone resulting in a goal can be computed, giving us the values of each state. Then, any player action that results in the puck moving from one zone to another would also be assigned a non-zero RIPP.

At the other extreme, the states might depend on the locations of all players on the rink, and even additional factors such as the game clock and score. Generally, any information that affects the probability of a team scoring could be included. In other words, the granularity of the state space is limited by the complexity of some sort of expected goals model.

4 Proof-of-Concept

To demonstrate the utility of our proposed framework, we implement a simple version of our framework on data from the 2021 NWHL season and the 2018 and 2022 Winter Olympics.

We focus our implementation on play-by-play event data only. While we do have a limited amount of tracking data available, this data requires significant cleaning to be useful for a very detailed state space. Specifically, the tracking data often has several players missing from view or incorrectly labelled. Additionally, since the tracking data is limited to power plays only, this may give us a biased expected goals model.

We implement a simple model for the state values whereby the value of a team having possession of the puck at a certain location is simply the probability of scoring a shot taken from that location. The value of the state for the opposite team is the negative of this probability. While this is a fairly simple choice of state value framework, it is fairly intuitive and easy to interpret. Below, we discuss the expected goals model we use to illustrate our framework.

4.1 Expected Goals Model

To even the most passive of hockey viewers, it is obvious that not all shots and scoring chances are created equally. In fact, it can be said that solely relying on shot count to estimate possession is a misleading way to analyze how well a team or player has played - a player who creates 50 long-distance shots is not worth nearly as much as a player who creates 10 close-range chances. In hockey and similar sports, the worth of a shot is estimated using an "xG" (expected goals) model, a model that takes contextual features into account and outputs the probability of a given shot resulting in a goal.

Expected goals models attempt to quantify the danger of a shot by using a myriad of contextual variables, including shot distance, angle, time of shot, number of skaters, goal differential, and more. Though many models use different pieces of information to draw conclusions, there are two variables that are considered critical to any expected goals model: distance and angle. Nearly all public xG models, such as [4], [5], and [6] include these as key features.

In our model, we use a polar coordinate system to compute for each shot the distance to the centre of net and the angle to the goal. Specifically, for a shot from coordinates (x, y), we have:

$$d = \sqrt{(x-189)^2 + (y-42.5)^2} \tag{1}$$

$$\theta = \arctan \frac{|y-42.5|}{|x-189|} \tag{2}$$

We pass these features into a logistic regression fit in R to develop our expected goals model. The coefficients of our selected logistic regression model are shown in Table 1. We see that the coefficient for Distance is negative, indicating that the probability of scoring a shot decreases as the distance to the goal increases. Similarly, the negative coefficient for Angle indicates that the probability of scoring a shot decreases as the angle increases. These results both align with our intuition.

Table 1: Coefficients of expected goals lx3ogistic regression model

	Coefficient	(Std. Error)
Constant	−1.158	0.211
Distance	−0.067	0.007
Angle	−0.0.893	0.231

Figure 1 shows a contour plot of the probability of scoring a shot from any given area on the ice. Areas closer to the net, or at a small angle to the centre of the net are given higher expected goals values by the model. These patterns align closely with our intuition.

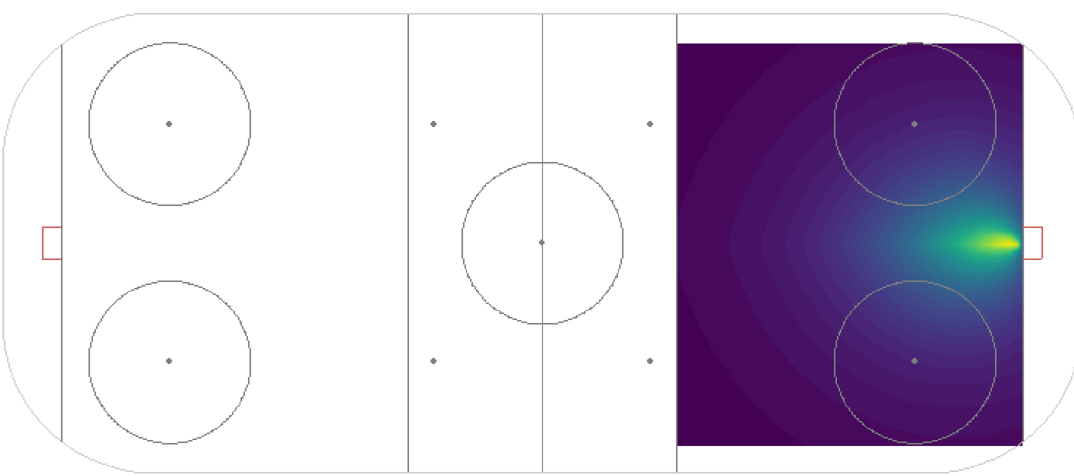

Figure 1: Contour plot of expected goals value. We only show the area where the expected goals value is significantly greater than zero.

4.2 State Transitions

We consider a variety of event types from the play-by-play data as state transitions in our model. Table 2 shows the locations we use as the start and end states to calculate the RIPP value for each event type.

Table 2: Start and End Values for Each Event Type

	Start Value	End Value
Play	Start loc. xG	xG at end loc. of pass
Incomplete Play	Start loc. xG	Opponent xG at end loc. of pass
Puck Recovery	-xG at previous event start loc.	xG at recovery loc.
Dump In/Out	Dump Start loc. xG	xG at recovery or -xG if not recovered
Faceoff Win	0.5*(Faceoff loc. xG)-0.5*(Opp. Faceoff loc. xG)	Next event loc. xG
Shot	xG at shot loc.	xG at next event loc.
Goal	1	xG at shot loc.

5 Results

Table 3 displays the players in our dataset with the highest RIPP per game, as estimated by the implementation described above. It is interesting to note that the most valuable player identified by the RIPP model, Mikyla Grant-Mentis, was the league MVP award winner in 2021.

Table 3: Highest-scoring players (min. 5 games played) according to RIPP per game

Team	Player	RIPP per game
Toronto Six	Mikyla Grant-Mentis	1.02
Toronto Six	Taylor Woods	0.96
Boston Pride	Samantha Davis	0.77
Olympic (Women) - Canada	Melodie Daoust	0.73
Boston Pride	Mallory Souliotis	0.73
Olympic (Women) - Finland	Susanna Tapani	0.720
Boston Pride	McKenna Brand	0.72
Boston Pride	Jillian Dempsey	0.69
Olympic (Women) - United States	Hilary Knight	0.67
Olympic (Women) - Canada	Rebecca Johnston	0.64

We have marketed the RIPP metric as a catch-all statistic, accounting for a number of indicators which together produce an accurate depiction of a player's value. However, it is useful to note that RIPP is a good predictor of a number of other metrics as well. For example, there is a strong linear correlation ($R = 0.83$) between a player's RIPP per game and their goals per game. This relationship is illustrated in Figure 2.

One strength of RIPP is its ability to create actionable insights for coaches and management. Figure 3 displays the isolated RIPP scores for various event types performed by Marie-Philip Poulin. As evidenced by this graph, scoring goals and puck recoveries are strong points in Marie-Philip Poulin's game. We can also see that Marie-Philip Poulin's incomplete plays and missed shots are a source of weakness in her game, as the RIPP score for this category is worse than the average player.

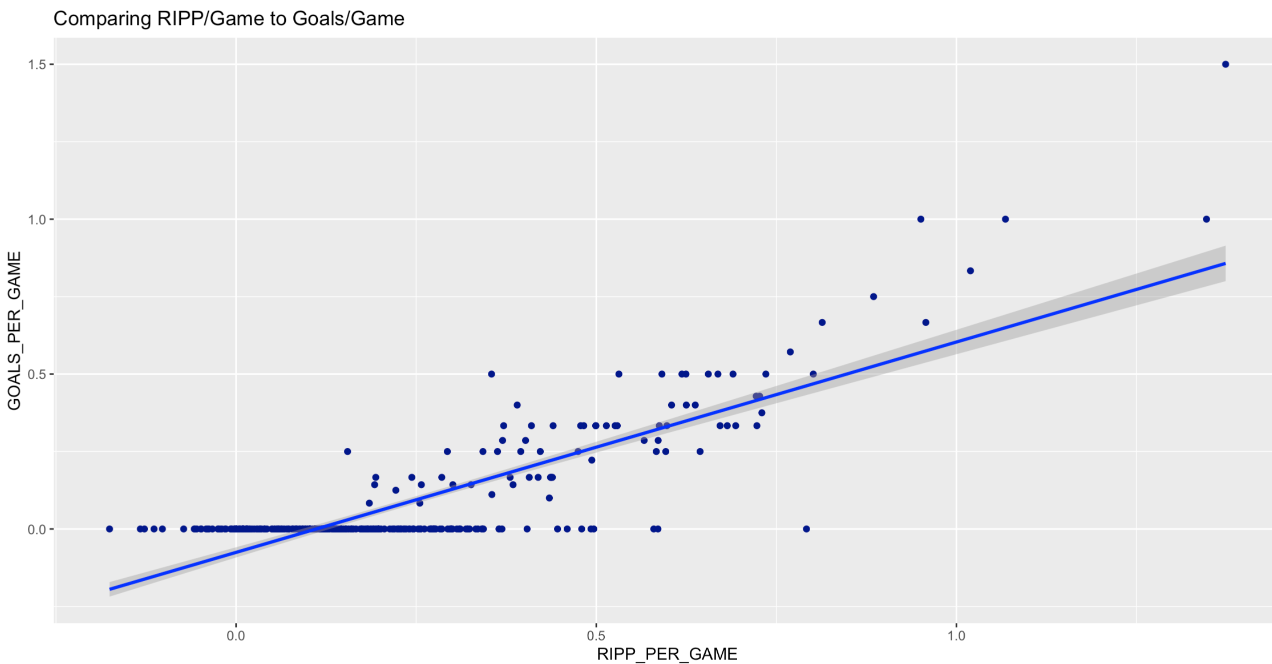

Figure 2: Goals per game vs. RIPP per game

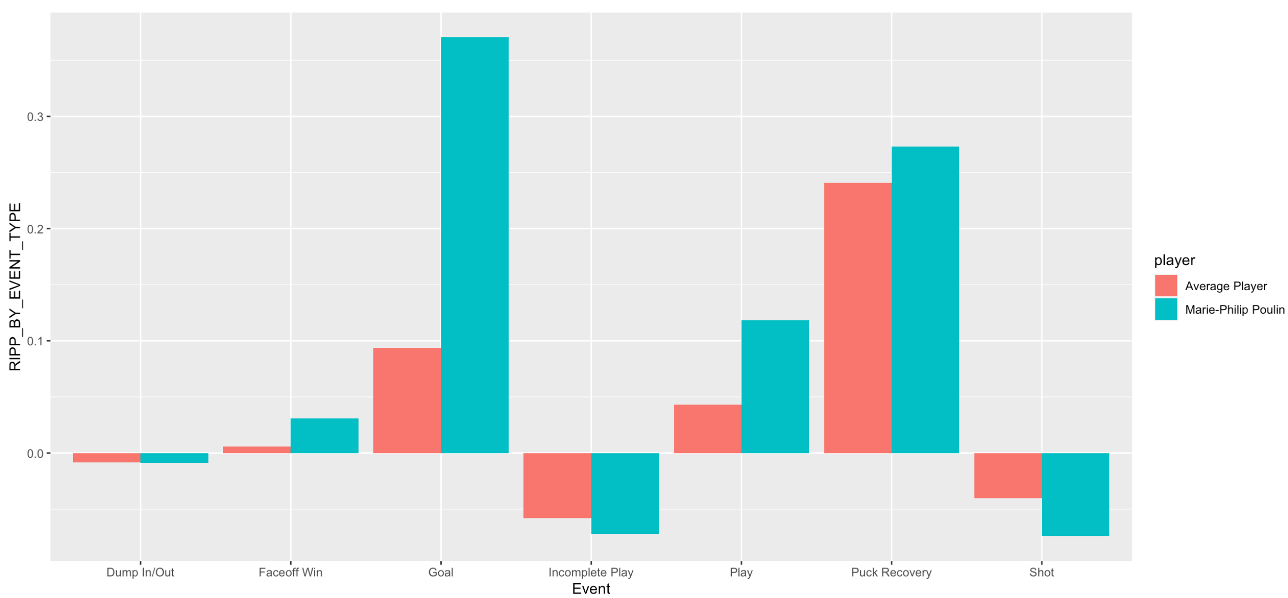

Figure 3: RIPP values per action type for Marie-Philip Poulin

6 Limitations

One significant limitation of the presented implementation of our framework is that only on-puck actions are valued. This means that most defensive actions and off-puck movement are not rewarded by our model at all, affecting the ability of our model to fully quantify the value of player actions. To fill this gap, more advanced state space and state evaluation models would be required that incorporate tracking data and off-puck player movement.

Secondly, using an expected goals model to attach values to states suffers from a plateau effect far from the goal. Since the expected goals value of a shot taken from most of the rink is near zero, except for near the opponent's goal, many actions in these regions would result in a very marginal value given to players. However, actions in these areas of the rink surely do affect the team's probability of scoring a goal, and should not be ignored in a more robust framework. To deal with this limitation, a different approach for valuing states can be used, such as that proposed by [2].

Thirdly, our current implementation does not yet extract all the information available from play-by-play data. For example, zone entries, penalties, and takeaways are not currently captured by our system. Most importantly, puck carries by players are also not rewarded. That is, we do not reward a player who takes the puck from a low expected goals location to a high expected goals location. Since puck carries are an important way for players to contribute to scoring chances, adding this information could result in improved player evaluation under our framework.

7 Conclusion

We present and implement a metric called "region-based isolated player performance", or RIPP. This metric rewards player actions with the difference in expected goals value for their team between the end and start of their action. Using a proof-of-concept, we demonstrate how our metric can be used to evaluate player actions and generate actionable insights for coaches and management. Lastly, we discuss several rooms for advancement, including a more advanced state space model relying on tracking data, or an improved state valuation framework.

References

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